PAPER

Evaluating the Probability of Power Loss in Ship Electric Propulsion Systems Based on Bayesian Belief Networks

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ABSTRACT

The development of smart and green ships has led to the wide use of electric propulsion systems, creating many safety problems. The ship electric propulsion system (SEPS) loses power frequently, creating significant risk in maritime transportation. This article proposed a probability evaluation method to assess SEPS power loss, based on Bayesian Belief Networks (BBNs). The BBN structure of power loss in a SEPS is considered the main component causing SEPS disruption. The prior probability and conditional probability tables of the model were generated using statistical data and expert judgment. A case study was conducted to illustrate the proposed model. Finally, a sensitivity analysis was used to identify several key indicators, including human factors, navigation conditions, winding failure, aging, and parameter setting. Compared with related research, the proposed method is rational and effective. As such, the method presented in this article provides a practical and flexible way to evaluate the probability of power loss in a SEPS. The model enables the safety manager to discover key influencing factors and components during ship operations, providing effective ways to reduce ship power loss.
Keywords: probability, evaluation, ship electric propulsion system (SEPS), Bayesian Belief Networks (BBN), power loss

Introduction

Environmental pollution is an important issue of global concern. The International Convention for the Prevention of Pollution from Ships (MARPOL) has proposed that ships should find new ways to reduce their collective greenhouse gas emissions (Lan et al., 2015). As such, traditional diesel-powered ships will soon be mitigated by renewable energy green ships (Zahedi et al., 2014). Most green ships apply electric propulsion systems, including solar energy ships, battery-powered ships, and super capacitor ships. Given their advantages related to energy conservation and operational flexibility, electric propulsion systems have been applied in almost all kinds of ships, including cruise ships, smart ships, engineering ships, and military ships. Electric propulsion systems are becoming a vital system for ships.

The development of smart and green ships has led to the wide use of electric propulsion systems, creating many security problems. Power losses in ship electric propulsion systems (SEPSs) occur frequently, creating significant risks in maritime transportation.

The rapid development of international seaborne trade brings a high likelihood of ship accidents. Several catastrophic shipping accidents have occurred in recent years. According to the accident statistics of China, more than 170 serious marine accidents occurred in 2018, resulting in 237 deaths, with a year-to-year increase of 24.7%. Using historical ship insurance claim statistics, the British Insurance Association (UK P&I CLUB) security department released a report summarizing common major accidents in 2016. The report showed that ship power loss has become a major risk leading to accidents. More than 700 accidents associated with ship power loss happened in the past years. Most of these accidents damaged third-party property (other ships, people, or docks), with large insurance claim values.

Generally, the modes of ship power loss can be divided into main engine power loss (68%), rudder power loss (19%), and other facts (Wu et al., 2017). For an electric powered ship, main engine power loss refers to propulsion power loss. Due to improvement in ship intelligence and automation, the propulsion system has become very complicated, and a variety of new failure modes have emerged. Moreover, the maritime environment is complex and dynamic, and SEPSs are prone to faults. These faults would result in many accidents, collisions, wrecks, oil spills, and ship damage. The propulsion system is widely defined as the heart of the vessel. The stability and reliability of a ship's electric propulsion system greatly affects efficient energy use, navigation security, and the safety of life at sea. (Barros & Diego, 2016).

The assessment of risks associated with power loss in a SEPS has recently attracted significant researcher attention. Accidents tend to be random and dynamic, making it hard to quantitatively evaluate the consequences of SEPS power loss. This study's motivation is to propose a probability evaluation model associated with SEPS power loss, using a Bayesian Belief Network (BBN). This enables safety managers to identify key influencing factors and components during ship operations, providing effective ways to reduce ship power loss.

The rest of this article is organized as follows. The Literature Review section provides a literature review of related research. The BBN Structure Considering Component Disruption section presents the BBN structure to evaluate the probabilities of SEPS power loss. It also presents the analysis of prior probability and conditional probability tables (CPTs) of the BBN. The Case Study section discusses a case study illustrating the proposed model and presents a sensitivity analysis and comparative analysis completed to verify the proposed model. Finally, general conclusions and limitations are provided in the Conclusion section.

Literature Review

Interest in the reliability of SEPSs has been increasing. Experts and scholars have conducted relevant studies on risk assessment approaches in shipping, risk analyses of ship loss power, reliability assessments, and failure mode analyses associated with electric power system.

Approach of Risk Assessment in Shipping

Many approaches have been applied to conduct maritime transportation risk analyses. Formal safety assessment (FSA) is a rational and systematic process for assessing risk and for evaluating the cost and benefit associated with reducing risk. FSA methodology is proposed to regulate shipping safety (Lois et al., 2004). In terms of risk analysis, quantitative risk assessments have attracted significant research attention. Soares and Teixeira (2001) reviewed different approaches used to quantify maritime transportation risk. Fu et al. (2016) evaluated the magnitude of consequences associated with coverage in flash fire accidents and estimated the potential risk of LNG-fueled vessel leakage using event-tree analysis. Yang et al. (2009) analyzed maritime security using fuzzy evidential reasoning.

Among these methods, BBN can easily represent the dependencies of events related with accidents by using CPTs (Friedman et al., 2000). BBN also has advantages over other models, including inverse inference ability (Li et al., 2014) and the ability to update the network with new observations. Hanninen (2014) reviewed the challenges and benefits of BBN when applied to maritime transportation risk assessment. Zhang et al. (2016) developed a BBN model to predict accident consequences in the Tianjin port. The research concludes that BBN is a well-suited methodology to support maritime risk assessment and decision-making. However, there are some problems associated with eliciting probabilities from experts and validating the model.

Risk Analysis of Ship Power Loss

When a ship loses power, ship equipment cannot work normally, including the rudder, engine, and navigation. Usually, effective measures can quickly recover ship power. However, due to development in ship intelligence and automation, power systems have become very complicated, introducing different failure modes. Moreover, hidden faults are hard to identify and address. Thus, the difficulty faced in maintaining the ship increases. Sometimes, ship power cannot be recovered in a timely manner. In these conditions, the ship is in danger and becomes a hazard to other ships. Once a ship loses power, it is no longer under control and is unable to maneuver as required by applicable rules and is therefore unable to keep out of the way of other vessels. The power loss can result in many kinds of accidents (including collision, wreck, oil spill, and ship damage). Table 1 lists some accidents caused by ship power loss.

The SOLAS Convention (the International Convention for the Safety of Life at Sea) specifies that ship propulsion systems should be restarted and able to operate within 30 min using an emergency generator. However, not all ships are equipped with an emergency generator, and not all emergency generators can provide the power needed by ship propulsion systems. In addition, human element

TABLE 1

Accidents caused by ship power loss.

Date	Place	Ship Losing Power	Accident Description
2017.7.21	Marmara Sea	"MAERSK KARACHI" cargo ship	Unable to navigate or anchor.
2017.7.7	Kaohsiung, Taiwan	"APL JEDDAH" container ship	Crashed into the dock, Ship hull was damaged.
2017.1.3	Pasir Gudang Johor Port, Malaysia	"APL DENVER" container ship	Collision accident, 300t oil spilt into the sea.
2016.6.12	Dongguan, China	"Lisha" cargo ship	Crashed into the dock, a barge ship wreck.
2016.5.9	Guanghzou Port, China	"Zhenpeng" tanker	Collision accident, ship hull was damaged.
2014.9.27	Zhejiang, China	"Minheng 69" container ship	Wreck.

is a contributory factor of numerous accidents. With the rapid and continuously running progress in electrical and electronic engineering on ships, the requirements of skills and practical abilities for seafarers have become increasingly advanced. The detailed description and new standards of competence for electrotechnical officers and electrotechnical ratings is added in STCW 78/2010 Convention (International Convention on Standards of Training, Certification and Watch Keeping for Seafarers), emphasizing the necessity of electronic staff (Mindykowski, 2017). In fact, it is a universal problem that the appropriately qualified staff is seriously inadequate.

Reliability Assessment of Electric Power Systems

Compared with traditional propulsion, electric propulsion has many advantages for ship operations, including higher stability and greater flexibility. The security of electric propulsion systems, however, has become a concern.

Failure mode effect and analysis is widely used to analyze ship machinery failures. Emovon et al. (2014) focused on the marine diesel engine, examining a total of 23 failure modes, including failures of the main bearing, piston, cylinder head, and crankshaft. The study identified the causes and effects of the failure modes. As suggested by the INCASS (Inspection Capabilities for Enhanced Ship Safety) FP7 EU-funded project, a machinery risk analysis (MRA) methodology is presented based on data acquisition and processing. A case study demonstrated the application of MRA.

Wang (2013) analyzed the failure modes associated with SEPSs. The study considered several major equipment items, including the transformer, inverter, and motor, and established a comprehensive evaluation index system for electric propulsion systems. An open-circuit fault will reduce electric system performance, through induced noise and vibrations. Often, this leads to a distortion of the current, leading to secondary problems (Choi et al., 2015).

Soares et al. (2015) identified risks associated with applying a battery power system. The full life cycle analysis identified the probability and severity levels considered in the risk analysis. The deteriorated power quality could affect ship safety. Tarasiuk and Mindykowski (2006) depicted the main features of ship electric power system and carried out research to deal with the problem of power quality estimation in ship networks. Tarasiuk (2009) presented the parameters for electric power quality reliable assessment and their permissible levels and proposed a new kind of instrumentation for power quality analysis called power quality estimator-analyzer. Mindykowski (2014) analyzed the existing ambiguities of the power quality assessment process and discussed the challenges to overcome them.

Barros and Diego (2016) discussed disturbances in ship electric power quality, including voltage and frequency fluctuations, voltage dips and swells, and harmonic distortion. The study also summarized the rules and regulations described in international standards and by marine classification societies.

The literature shows that research on ship power loss is limited. In addition, the risk assessment research about ship power loss does not represent how different influencing factors affect the final power loss. Furthermore, most of the methods do not provide results quantitatively.

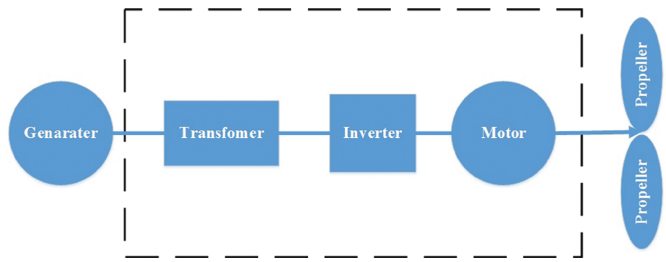
BBN Structure Considering Component Disruption

SEPS Structure

Figure 1 shows that a SEPS generally consists of three main parts:

FIGURE 1

A typical SEPS structure.



the electric transformer, inverter, and motor. The generator and propellers are important components for electric input and output, respectively. There are many failure modes for a SEPS. This article is focused on the power loss contingency. As such, the study only considers disruption contingencies leading to power loss. From the perspective of component disruption, the following five events lead to SEPS power loss: input power disruption, cable disruption, transformer disruption, inverter disruption, and motor disruption.

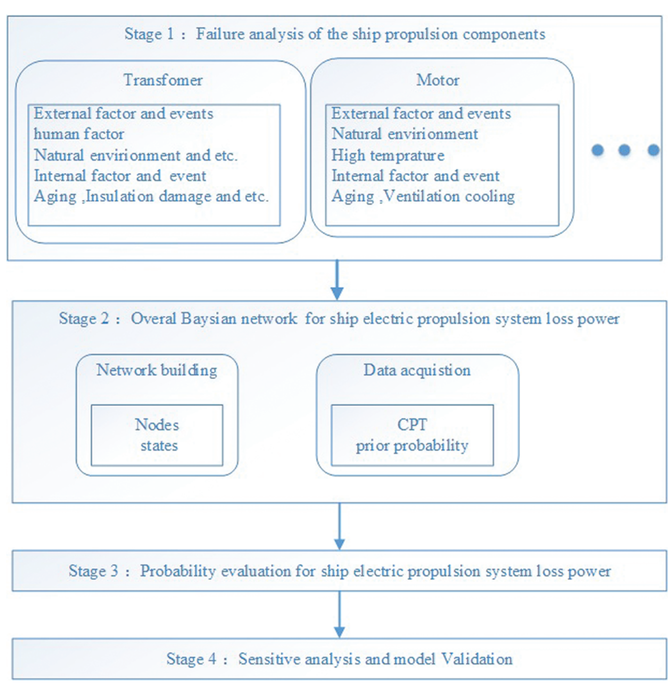
Framework of the Proposed Method

In order to evaluate the probability of power losses in SEPS, a method based on BBN is proposed. Figure 2 presents the framework of the proposed method to evaluate the probability of power loss in a SEPS.

The first stage depicts the main components associated with SEPS disruption by summarizing the influencing factor and event nodes and the relationship between them. The nodes include external factors (those factors beyond the ship itself, such as human error and environmental factors) and internal factors (those factors involved with the ship itself, such as insulation damage and winding deformation). Then, an overall BBN structure is developed to describe SEPS power loss by combining the component disruptions. The study also analyzes the prior probability and CPTs. The third stage provides a case study. It is followed by a sensitivity analysis and comparative analysis to verify the proposed model for the fourth stage.

FIGURE 2

Framework for the probability evaluation of power loss in a SEPS.



BBN Structure of Components

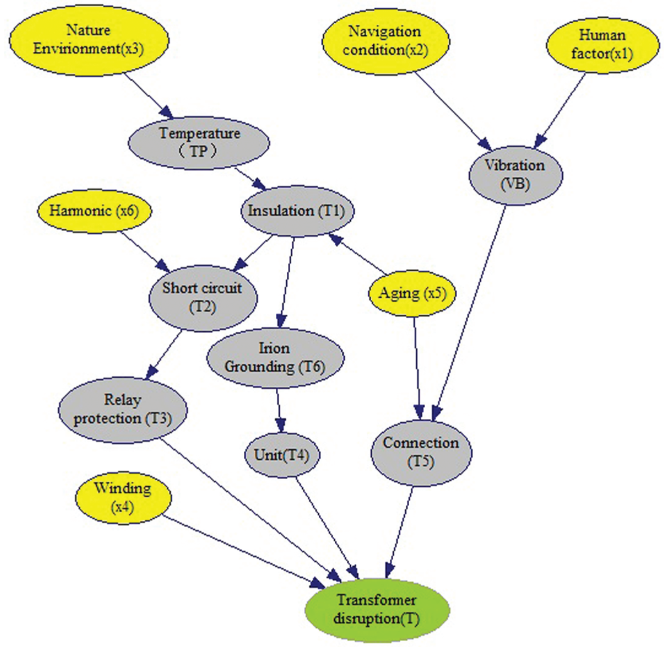
Previous studies indicate that many researchers have studied the reliability and failure modes of ship machinery, providing adequate statistical data and fault tree models in terms of SEPS components. This article is focused on power loss-related accidents in a SEPS. Challenges include identifying the related factors and events and developing the logical model.

As discussed in the SEPS Structure section, five events result in SEPS power loss: input power disruption, cable disruption, transformer disruption, inverter disruption, and motor disruption. However, it is generally accepted that the three key components in a SEPS are the transformer, inverter, and motor.

GeNIe is a versatile and user-friendly software tool for graphical decision-theoretic models, allowing the user to construct influence diagrams and offering value-of-information analysis. GeNIe could implement Bayesian networks by showing graphically the variations and computing the impact of observing values. Thus, this section presents the BBN structures of the three disruptive components, generated by GeNIe. The structures are based on logical models, expert

FIGURE 3

The BBN structure for SEPS transformer disruption.



opinions, literature review, or the combinations of the above.

The BBN is a structure network consists of three kinds of nodes (target node, event nodes, and factor nodes) and the relationship between them (see Figure 3). The target node refers to the final event, SEPS power loss, denoted by blue ellipse. The yellow ellipse refers to the factor node. The gray ellipse refers to the event node, and the green ellipse refers to the component disruption (which is a special event node, directly resulting in the final event).

Transformer Disruption

The transformer's operation status relates to the state of transformer winding, relay protection, unit, and connection. For example, if the winding gets deformed, the transformer is disrupted. According to the causal relationship of the failure event, there are six influencing factors: human factor, navigation condition, nature environment, winding, aging, and harmonic wave (simplified as harmonic). Figure 3 shows the BBN structure of the transformer disruption.

Table 2 presents the six influencing factor nodes' states and eight event nodes' states. For example, the human factor states are determined based on their reliability. When the seafarer has reliable skills and physical state, the human factor state is set as reliable. Otherwise, the state of human factor is set as unreliable.

Figure 3 and Table 2 show that serious harmonic problems or damaged insulation affect the short circuit. Furthermore, short circuiting of the transformer could trip the transformer relay, causing transformer disruption eventually.

Inverter Disruption

As with transformer disruption, Figure 4 establishes the BBN structure of the converter disruption. The state of the voltage and relay protection relate to the operational status. Voltage problems will lead to inverter disruption. Based on the causal relationship of the failure event, eight influencing factors are included, including navigation conditions, the natural environment, human factors, aging, parameter setting (simplified as parameter), ventilation cooling, motor overload, and grounding.

Table 3 presents the eight influencing factor node states and 13 event nodes. For example, the states of the aging node are determined based on ship age. According to Koromila et al. (2014), if the ship age is between 1 and 5 years, the state of ship aging is set as new; if the ship age is between 6 and 25 years, the state of ship aging is set as middle age; and if the ship age is over 25 years, the state of ship aging is set as old.

Figure 4 and Table 3 show that sudden changes in the navigation conditions or a lightning strike could create a sudden drop in voltage. Furthermore, a sudden drop in voltage will lead to voltage problems, which may lead to converter disruption.

Motor Disruption

Figure 5 presents the BBN structure of the motor disruption. The state of winding and relay protection relate to the operational status. A winding burnout state will lead to motor disruption. Based on the causal relationship of the failure event, there are six influencing factors: the natural environment, aging, ventilation cooling, friction, leakage, and overvoltage.

Table 4 presents the six influencing factor node states and five event nodes. For example, the states of friction are determined based on the extent of the friction. If the fixed

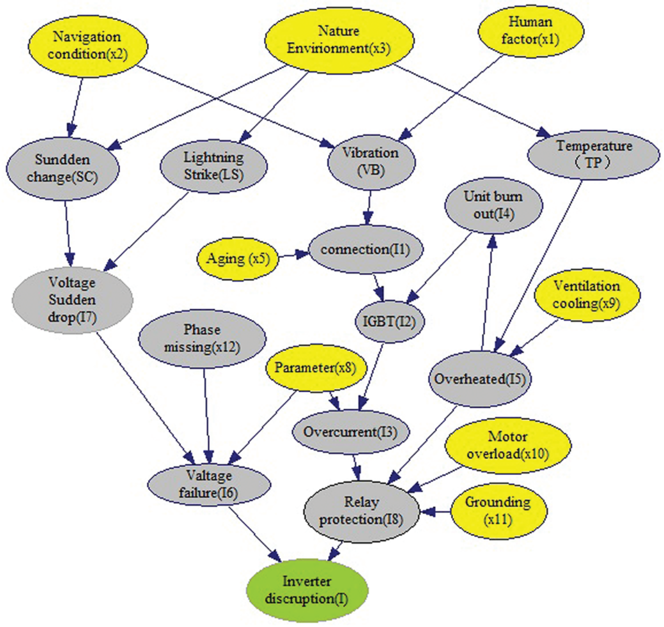
TABLE 2

Detailed descriptions of the nodes related to transformer disruption (T).

Layer	Nodes Type	Nodes Name	States	Explanation
External layer	Factor nodes	Human factor (X1)	Reliable	The skill and physical state of seafarer is reliable.
			Unreliable	The skill and physical state of seafarer is unreliable.
		Navigation condition (X2)	Good	The navigation condition is good.
			Normal	The navigation condition is normal.
			Bad	The navigation condition is bad.
		Nature environment (X3)	Good	The natural environment is good.
			Normal	The natural environment is normal.
			Bad	The natural environment is bad.
	Event nodes	Temperature (TP)	High	The temperature is much higher than the system can bear.
			Moderate	The temperature is in the range the system can bear.
		Vibration (VB)	Serious	Over the range of the standard level (vibration standard in China Classification Society [CCS]).
			Normal	In the range of the vibration of ship propulsion system standard level (vibration standard in CCS).
Internal layer	factor nodes	Winding (X4)	Deformed	The winding of transformer is out of shape
			Undeformed	The winding of transformer is in good condition.
		Aging (X5)	New	The ship age is 1–5 years.
			Middle age	The ship age is 6–25 years.
			Old	The ship age is higher than 26 years.
		Harmonic (X6)	Serious	The harmonic wave is serious in the electric circuit.
			Normal	The harmonic wave is in the appropriate range of the electric circuit.
	Event nodes	Insulation (T1)	Damaged	The insulation of transformer is damaged.
			Undamaged	The insulation of transformer is not damaged.
		Short circuit (T2)	Yes	Short circuit of transformer.
			No	The circuit is normal of transformer.
		Relay protection (T3)	Success	Tripping of the transformer relay.
			Failure	Tripping failure of the transformer relay.
		Unit (T4)	Breakdown	The unit of transformer is breakdown.
			Good	The unit of transformer is in good condition.
		Connection (T5)	Disconnected	Connection failure between transformer components.
			Connected	Connection is normal between transformer components.
		Iron grounding (T6)	Normal	More than one iron core of transformer touches the ground.
			Abnormal	One iron core of transformer touches the ground.

FIGURE 4

The Bayesian network for SEPS converter disruption.



rotor friction is significant, the state of friction is set as serious. If the fixed rotor friction is slight, the state of friction is set as slight.

Figure 5 and Table 4 show that ventilation cooling failure, leakage, and overvoltage could result in winding burnout. Furthermore, winding burnout will lead to motor disruption.

The Overall BBN Structure

Figure 6 shows the overall BBN structure developed by combining the five components of disruption. There are 15 factor nodes (in yellow ellipses) and 27 event nodes (five nodes are subevent nodes in green ellipses).

TABLE 3

Detailed descriptions of the nodes related to inverter disruption (I).

Layer	Nodes Type	Nodes Name	States	Explanation
External layer	Factor nodes	Human factor (X1)	Reliable	The skill and physicality of seafarer is reliable.
			Unreliable	The skill and physicality of seafarer is unreliable.
		Navigation condition (X2)	Good	The navigation condition is good.
			Normal	The navigation condition is normal.
			Bad	The navigation condition is bad.
		Natural environment (X3)	Good	The natural environment is good.
			Normal	The natural environment is normal.
			Bad	The natural environment is bad.
	Event nodes	Temperature (TP)	High	The temperature is much higher than the system can bear.
			Moderate	The temperature is in the range the system can bear.
		Vibration (VB)	Serious	Over the range of the standard level.
			Normal	In the range, the vibration of ship propulsion system standard level; vibration in cabins of CCS.
		Sudden change (SC)	Yes	Sudden change of navigation condition.
			No	Navigation condition is well.
		Lightning strike (LS)	Yes	Lightning strike appear.
			No	No lightning strike

continued

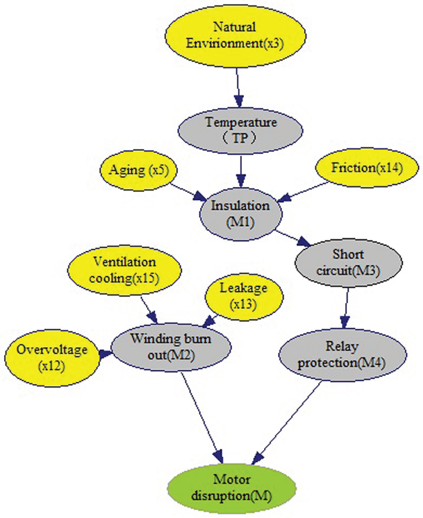
TABLE 3

Continued

Layer	Nodes Type	Nodes Name	States	Explanation
Internal layer	Factor nodes	Aging (X5)	New	The ship age is 1–5 years.
			Middle age	The ship age is 6–25 years.
			Old	The ship age is higher than 26 years.
		Parameter (X8)	Reasonable	The parameter of inverter is reasonable.
			Unreasonable	The parameter of inverter is unreasonable.
		Ventilation cooling (X15)	Bad	The Ventilation cooling fails.
			Good	The Ventilation cooling is good.
		Motor overload (X10)	Healthy	97.38%
			Marginal	2.59%
			At-risk	0.03%
		Ground (X11)	Failure	The grounding failure of inverter.
			Success	The grounding is normal of inverter.
		Phase missing (X9)	Yes	Input voltage phase is missing.
			No	Input voltage is well.
	Event nodes	Connection (I1)	Disconnect	The drive line of inverter is disconnected.
			Connected	The drive line of inverter is connected.
		IGBT (I2)	Open	The Insulated Gate Bipolar Transistor (IGBT) of inverter is open circuit.
			Normal	The IGBT of inverter is normal.
		Overcurrent (I3)	Yes	Overcurrent happens in inverter.
			No	Overcurrent does not happen in inverter.
		Unit burn out (I4)	Yes	The unit of inverter is burnt out.
			No	The unit of inverter is well.
		Overheated (I5)	Yes	The inverter is overheated.
			No	The inverter is well.
		Voltage sudden drop (I6)	Yes	A sudden drop of voltage happens.
			No	There is no sudden drop of voltage.
		Voltage problem (I7)	Wrong	The voltage on inverter is wrong.
			Well	The voltage on inverter is well.
		Relay protection (I8)	Success	Tripping of the transformer relay.
			Failure	Tripping failure of the transformer relay.

FIGURE 5

The BBN structure for SEPS motor disruption.



Prior Probabilities and CPTs of BBN Model

Determining prior probabilities and CPTs is the most important and most difficult step for the proposed BBN method. The prior probabilities and CPTs can be obtained using statistical data and expert judgment. Here, the CPTs are used as an example to illustrate methods to obtain the data. The state of some event nodes is Yes or No, meaning that the event may happen or not. These specific nodes all have probabilities of 0 or 1. Using node I7 (sudden drop in voltage) as an example, Table 5 shows the CPT table. Either "sudden change" or "lighting strike happens" will lead to the direct sudden drop in voltage, at a probability of 1.

For most event nodes, the probability of each state is between 0 and 1. The most widely used method is using available statistical data, from experimental results or from reference material. For instance, Yang et al. (2004) obtained transformer insulation reliabilities under different conditions using a computer experiment. Table 6 provides the CPT for insulation. If the environmental temperature is high, the probability of transformer insulation damage with a new ship is 6.21%. For a middle-aged ship, the probability of transformer insulation damage is 28.90%.

For some event nodes, there is no statistical data for CPTs. In these cases, the expert judgment method is applied. To obtain CPTs, 10 experts from universities, companies, and maritime administration were invited to provide judgments based on their experience. The average value is used to develop the CPTs. Table 7 provides the CPT of sudden change as an example.

Specifically, five events result in direct SEPS power loss: input power disruption, cable disruption, transformer disruption, inverter disruption, and motor disruption. Component properties differ; as such, the probabilities of power loss caused by component disruption also differ. The power loss probability can be derived based on the recovery time and frequency of the components failure (Lin, 2006; Wang, 2013). Moreover, the component functions and statuses differ across SEPSs, which alters the degree of importance of different nodes. They are determined using expert judgment. Table 8 shows the probability of power loss and the degree of importance of the five components.

Table 8 shows that when the cable is disrupted, the probability of SEPS power loss is the highest, at 75.63%. With respect to the degree of importance, the transformer is the most important component in the SEPS, as it has the greatest impact on the probability of SEPS loss power. As such, the safety manager should pay more attention to transformer disruption.

Based on Table 8, we can calculate the conditional probability of SEPS power loss using the equation $P = \sum_{i=1}^{n} \omega_i p_i$, where i denotes the number of components, ω_i denotes the degree of importance of the ith component disruption, and p_i denotes the probability of power loss of the ith component disruption. Table 9 shows the CPT of SEPS power loss (D: disruption; W: well).

The proposed method to evaluate the probability of SEPS power loss has the following strengths. First, it provides a graphical structure to represent how the influencing factors and event affect the SEPS power loss, comprehensively considering external and internal factors, machinery, and management failure. Second, the proposed method can address both historical or statistical data and knowledge from expert judgment. Third, any probability distribution of these nodes in BBN can be implemented. Finally, it is sufficiently flexible to consider new influencing factors and events. The prior probability and CPTs can also be freely updated in the graphical structure. It indicates the method can be applied to evaluate the probability of SEPS power loss over time and in different places.

Case Study

A case study was conducted to illustrate the proposed risk assessment model for SEPS power loss. A 500-ton pure electric cargo ship in Huzhou, China, was selected as the example. The ship is a bulk cargo ship, equipped with a super capacitor

TABLE 4

Detailed descriptions of the nodes related to motor disruption (M).

Layer	Nodes Type	Nodes Name	States	Explanation
External layer	Factor	Natural environment (X3)	Good	The natural environment is good.
			Normal	The natural environment is normal.
			Bad	The natural environment is bad.
	Event	Temperature (TP)	Too high	The temperature is much higher than the system can bear.
			Moderate	The temperature is in the range the system can bear.
Internal layer	Factor	Aging (X5)	New	The ship age is 1–5 years.
			Middle age	The ship age is 6–25 years.
			Old	The ship age is higher than 25 years.
		Ventilation cooling (X15)	Bad	The ventilation cooling fails.
			Good	The ventilation cooling is good.
		Overvoltage (X12)	Yes	The voltage on motor is too high.
			No	The voltage on motor is appropriate.
		Leakage (X13)	Yes	Water or oil leakages happen.
			No	No water or oil leakages happen.
		Friction (X14)	Seriously	Fixed rotor friction is serious.
			Slightly	Fixed rotor friction is slight.
	Event	Insulation (M1)	Damaged	The insulation of stator winding is damaged.
			Undamaged	The insulation of stator winding is well.
		Winding burn out (M2)	Yes	The stator winding is burned out.
			No	The stator winding is normal.
		Short circuit (M3)	Yes	Short circuit of motor.
			No	The circuit is normal in the motor.
		Relay protection (M4)	Success	Tripping of the transformer relay.
			Failure	Tripping failure of the transformer relay.

and lithium battery in the engine, and can be considered a typical green ship. The ship length is 38 m, the DWT is 500 ton. Due to the battery charging requirement, the ship sails only in Zhejiang Province lake.

Prior Probabilities

According to the proposed model for evaluating the probability of SEPS power loss based on BBN, we can identify the prior probabilities and CPTs. Based on statistical data and expert judgment, Table 10 shows the prior probabilities of factor nodes. The details of other CPTs are not presented due to their large size.

Results

By introducing the prior probabilities and the CPTs into the BBN structure, we can obtain the probability of SEPS power loss using the Bayesian probability algorithm. The GeNle software facilitates this calculation process. Figure 7 shows the graphical structure of the result. The probability of SEPS power loss is 0.07, meaning that for the electric ship based on the given evidence, the number of occurrences of SEPS power loss is 0.07. It is concluded that the probability of SEPS power loss for the case study is not very high.

FIGURE 6

The overall BBN structure for SEPS power loss.

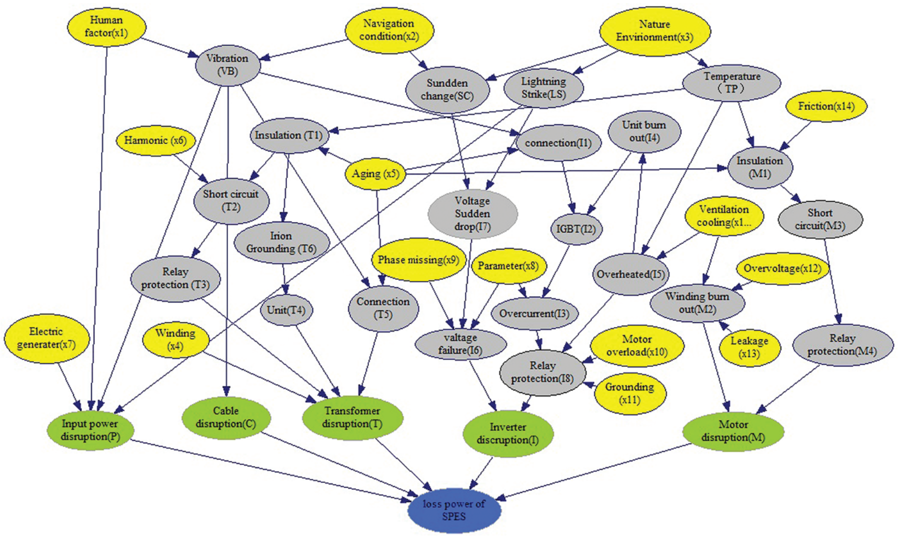


TABLE 5

The CPT of sudden drop in voltage (I7).

Sudden Change (SC)		Yes		No	
Lightning Strike (LS)		Yes	No	Yes	No
Voltage sudden drop (I7)	Yes	1	1	1	0
	No	0	0	0	1

TABLE 6

The CPT of transformer insulation (T1).

Temperature (HT)		High			Moderate		
Aging (X5)		New	Middle Age	Old	New	Middle Age	Old
Insulation (T1)	Damaged	6.21%	28.90%	31.84%	0	8.44%	12.85%
	Undamaged	93.77%	71.10%	68.16%	1	91.56%	87.15%

TABLE 7

The CPT of sudden change (SC).

Nature Environment		Good			Normal			Bad		
Navigation Environment		Good	Normal	Bad	Good	Normal	Bad	Good	Normal	Bad
Sudden change	Yes	0	2%	5%	6%	7%	8%	9%	11%	15%
	No	1	98 %	95%	94%	93%	92%	91%	89%	85%

Sensitivity Analysis and Validation

A sensitivity analysis is an effective way to determine the key indicators having a significant impact on the probability of SEPS power loss. The results are compared, given that a certain indicator is under different states. The parameter of the sensitivity value is proposed to describe the degree of influence on the probability by the indicators (Zhang et al., 2016). The sensitivity value is defined by Equation 1:

$$S_k = \frac{1}{N_k} \sum_{i=1}^{Nk} \frac{|U_i - U|}{1 - p_i} \tag{1}$$

In this expression, S_k is the sensitivity value of a node, N_k is the number of states, U_i is the utility value of the consequence, given that the node is under the ith state, U is the average utility value of consequence, and p_i is the prior probability of the node under the ith state.

With GeNle software, we use the "set evidence" function on the node, right-clicking on the node generates

TABLE 8

The power loss probability and important degree of components.

Component	Probability of Power Loss (p_i)	Degree of Importance (ω_i)
Input power	29.24%	0.10
Cable	75.63%	0.18
Transformer	55.2%	0.33
Inverter	68.40%	0.18
Motor	60.2%	0.21

the probability of SEPS power loss. For example, when inputting the prior information of “navigation” as good, the probability of a good state is 100%. It is the recorded result for the probability of SEPS power loss. Then, based on clear evidence, we set the prior information about “navigation” as normal or bad and record the corresponding result. Introducing the results and probabilities into Equation 1 gets the sensitivity value. All nodes can be treated in the same way, including factor nodes and event nodes. Figure 8 presents the top five sensitivity values for the factor nodes. The sensitivity value for human factor, navigation, winding, aging, and parameter is 5%, 4%, 7%, 19%, and 13%, respectively.

Figure 8 shows that the following factor nodes impact the probability of SEPS power loss significantly: the human factor, navigation conditions, winding, aging, and the parameter. The results indicate that the probability of SEPS power loss will be much higher for an old ship than a new one. The probability of power loss is also impacted by human error, bad navigation conditions, deformed winding, and unreasonable parameter. The result shows that risk management benefits from paying special attention to human error, navigation conditions, deformed winding, ship age, and parameter setting. As the development of green and intelligent ships advances, appropriately qualified staff is becoming more and more important for modern ship safety. The skills and practical abilities of electronic staff should be further enhanced (Mindykowski, 2017). Therefore, maritime education and training is an effective way to reduce probability of SEPS power loss.

The parameter setting depends on the ship electrician’s experience and knowledge. Usually, the inverter is disrupted because of too low current limit or too short acceleration time. Thus, training seafarers on electric management is an effective way to reduce ship power loss. In contrast, other factors are less sensitive to the probability of SEPS power loss. It indicates that the probability of SEPS power is similar whether the friction is serious or slight, as well as the other factor nodes.

The conclusion emerging from the sensitivity analysis is consistent with the real-world situation (Wang, 2013). In the case study, the probability of power loss (7%) is consistent with the results in other studies. Most expert report that the probability of electric system power loss is less than 10%. Yu and Gao (2011) conducted a statistical data analysis of transformer failure over 5 years, concluding that the probability of transformer failure is 3.47%. Allan and Billinton (2000) studied the reliability of power systems, concluding that the probability of the electric system forced outage rate is 1%. Ding et al. (2003) used a mathematical experiment to calculate the probability of electric system power loss as 8%. Therefore, the proposed method to evaluate the probability of SEPS power loss is shown to be rational and effective.

Conclusion

The development of smart and green ships has led to the wide use of electric propulsion systems, creating many security problems. Power loss in SEPSs occurs frequently, creating significant risk in maritime transportation.

The main contribution of this article is that it proposed a BBN model to assess the risk associated with SEPS power loss. The model focuses on evaluating probabilities. The proposed BBN model systematically synthesizes available knowledge about SEPS power loss, including data about component failures, probability data associated with node states, and expert knowledge. The study summarizes the merits of the proposed method for evaluating the probability of SEPS power loss. These merits include the model’s flexibility and feasibility. A case study was conducted to illustrate the proposed model. The probability of SEPS power loss in the case study was 0.07. A sensitivity analysis was used to identify several key indicators: human factors, navigational conditions, winding, aging, and parameter. Compared with related research, the proposed method was demonstrated to be rational and effective. As such, this article’s method provides

TABLE 9

The CPT of SEPS power loss.

Component	State															
Input power	D															
Cable	D								W							
Transformer	D				W				D				W			
Inverter	D		W		D		W		D		W		D		W	
Motor	D	W	D	W	D	W	D	W	D	W	D	W	D	W	D	W
Loss power powerful	0.60	0.47	0.47	0.35	0.41	0.29	0.29	0.17	0.46	0.33	0.33	0.21	0.27	0.15	0.15	0.03
	0.40	0.53	0.53	0.65	0.59	0.71	0.71	0.83	0.54	0.67	0.67	0.79	0.73	0.85	0.85	0.97
Component	**State**															
Input power	W															
Cable	D								W							
Transformer	D				W				D				W			
Inverter	D		W		D		W		D		W		D		W	
Motor	D	W	D	W	D	W	D	W	D	W	D	W	D	W	D	W
Loss power powerful	0.57	0.44	0.44	0.32	0.38	0.26	0.26	0.14	0.43	0.30	0.30	0.18	0.24	0.12	0.12	0
	0.43	0.56	0.56	0.68	0.62	0.74	0.74	0.86	0.57	0.70	0.70	0.82	0.76	0.88	0.88	1

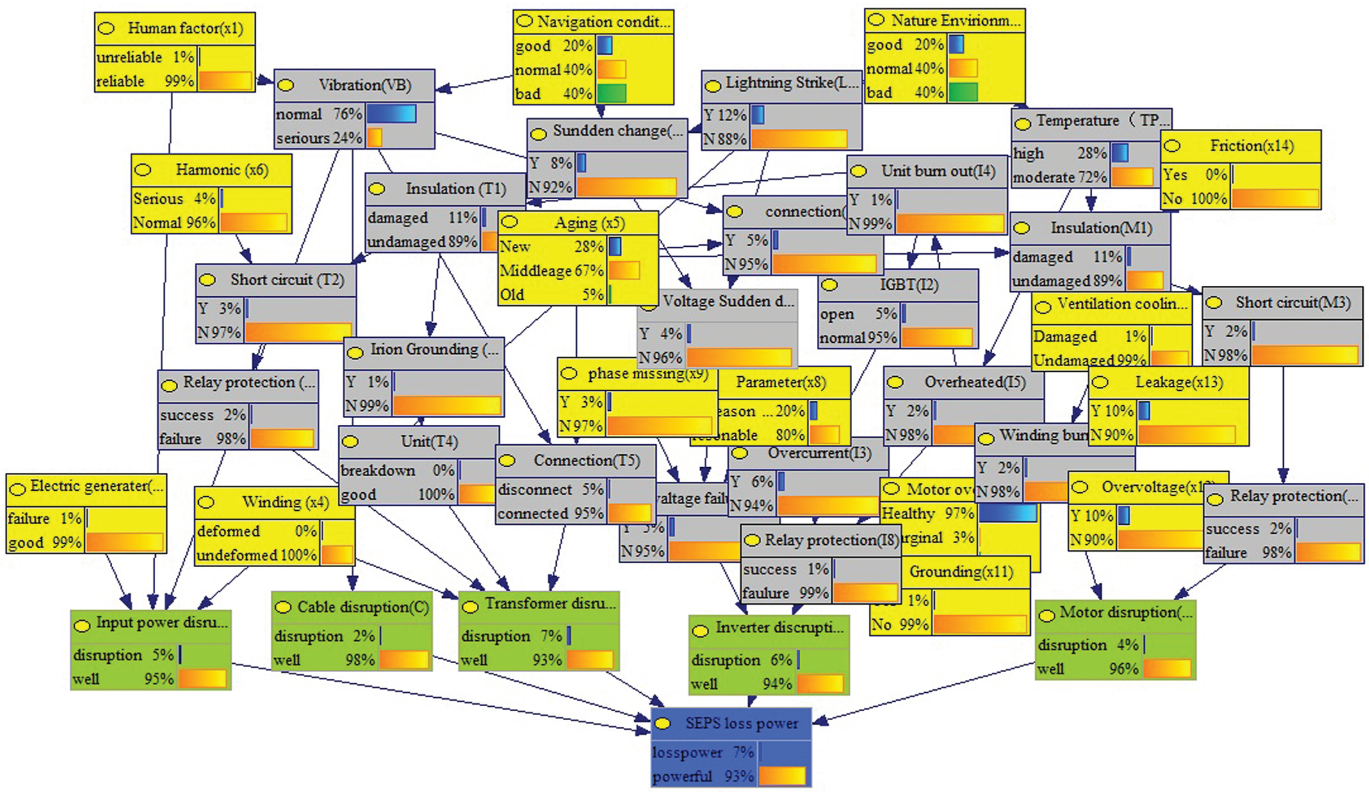
TABLE 10

The prior probabilities of factor nodes.

Nodes	States	Prior Probabilities	Data Source
Human factor (X1)	Unreliable	0.56%	Jiang et al. (2017)
	Reliable	99.44%	
Navigation condition (X2)	Good	20.00%	Wu et al. (2017)
	Normal	40.00%	
	Bad	40.00%	
Natural environment (X3)	Good	20.00%	Wu et al. (2017)
	Normal	40.00%	
	Bad	40.00%	
Winding (X4)	Deformed	0.30%	Yu and Gao (2011) Jongen et al. (2007)
	Undeformed	99.70%	
Aging (X5)	New	27.87%	Koromila et al. (2014)
	Middle age	67.23%	
	Old	4.90%	
Harmonic (X6)	Serious	4.00%	Pezzani et al. (2014) Barros & Diego (2016)
	Normal	96.00%	
Electric generator (X7)	Failure	1.21%	The INCASS project
	Good	98.79%	
Parameter (X8)	Reasonable	70.00%	Expert judgment
	Unreasonable	30.00%	
Phase missing (X9)	Yes	3.00%	The INCASS project
	No	97.00%	
Motor overload (X10)	Healthy	97.38%	Allan and Billinton (2000)
	Marginal	2.59%	
	At-risk	0.03%	
Grounding (X11)	Yes	0.83%	The INCASS project
	No	99.17%	
Overvoltage (X12)	Yes	10.00%	Expert judgment
	No	90.00%	
Leakage (X13)	Yes	10.00%	Expert judgment
	No	90.00%	
Friction (X14)	Yes	0.06%	The INCASS project
	No	99.94%	
Ventilation cooling (X15)	Damaged	0.57%	The INCASS project
	Undamaged	99.43%	

FIGURE 7

The BBN of the SEPS power loss.

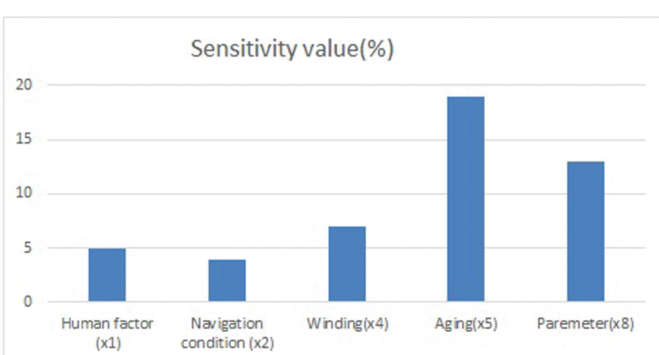


a practical and flexible way to evaluate the probability of SEPS power loss. The model enables safety managers to identify key influencing factors and components during ship operations, providing effective ways to reduce ship power loss.

In closing, while this study's model was only verified using the case study in Huzhou, the model should be tested using additional case studies. Further validation and adjustments are necessary to facilitate further applications.

FIGURE 8

The top five sensitivity values of factor nodes.



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